Everything I Disagree With is #FakeNews:

Correlating Political Polarization and Spread of Misinformation

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- News consumption after Online Social Networks:

Reputation
matters less

Profits comes
from clicks

Recommended
content

- Due to this, two phenomena have their impact increased:

Opinion Polarization

Spread of Misinformation

Opinion Polarization

"the extent to which opinions on an issue are opposed in relation to some theoretical maximum"

- Recommendation algorithms may limit users to ideologically diverse content.
- System may fuel partisan news, thus increasing polarization.

Motivation

"misinformation is false or incorrect information, that is spread intentionally or unintentionally"

Spread of Misinformation

- Made easier by the decrease in the accountability of sources.
- Bots may be employed to disseminate misinformation.

- The media suggests an interaction between these:

Opinion
Polarization

Spread of
Misinformation

- The media suggests an int

P

Stop Calling Everything “Fake News”

Journalists are blurring several problems into one—and making it impossible to solve.

By Will Oremus

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Spread of Misinformation

- But also previous studies also do:

Opinion Polarization

polarized groups are more susceptible to the dissemination of misinformation

Spread of Misinformation

- But also previous studies also do:

Opinion Polarization

the dissemination of misinformation plays a key role in creating polarized groups

Spread of Misinformation

- Can this interaction happen in some other way?

Motivation

"everything I disagree with is fake news"

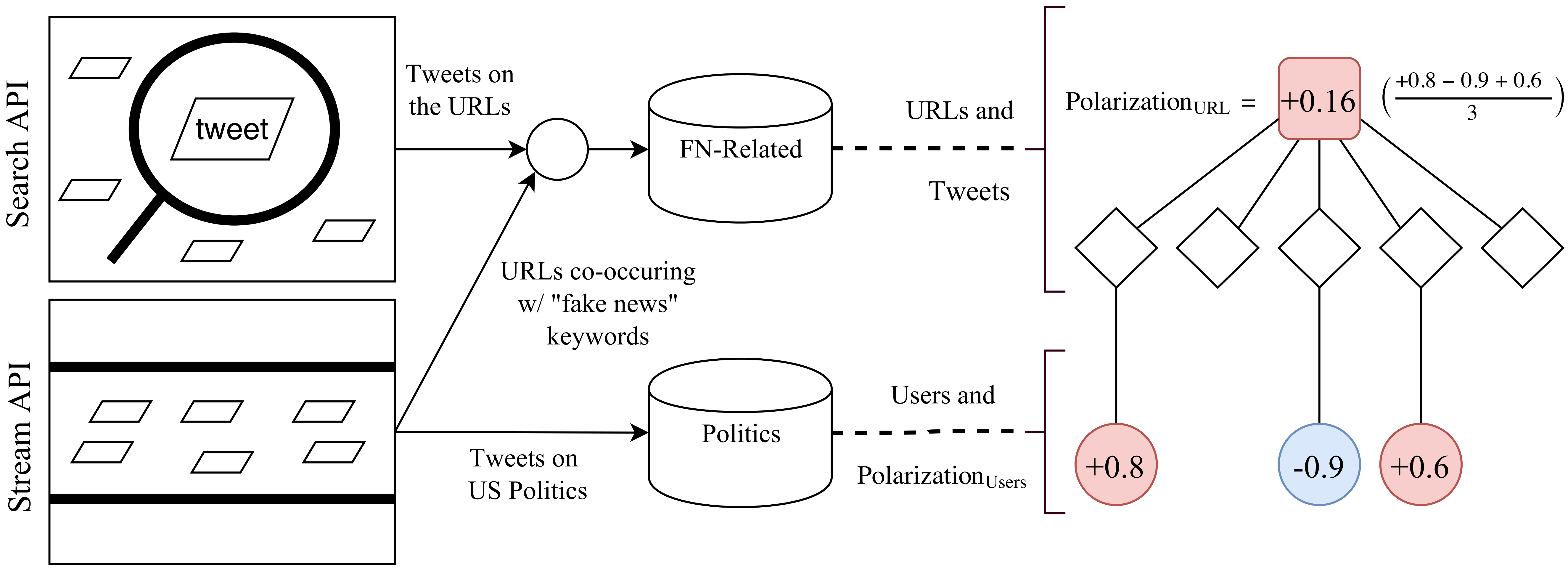
???

- Users designate incorrectly classify sources of misinformation due to disagreement.
- Alternate narratives of "what is true"

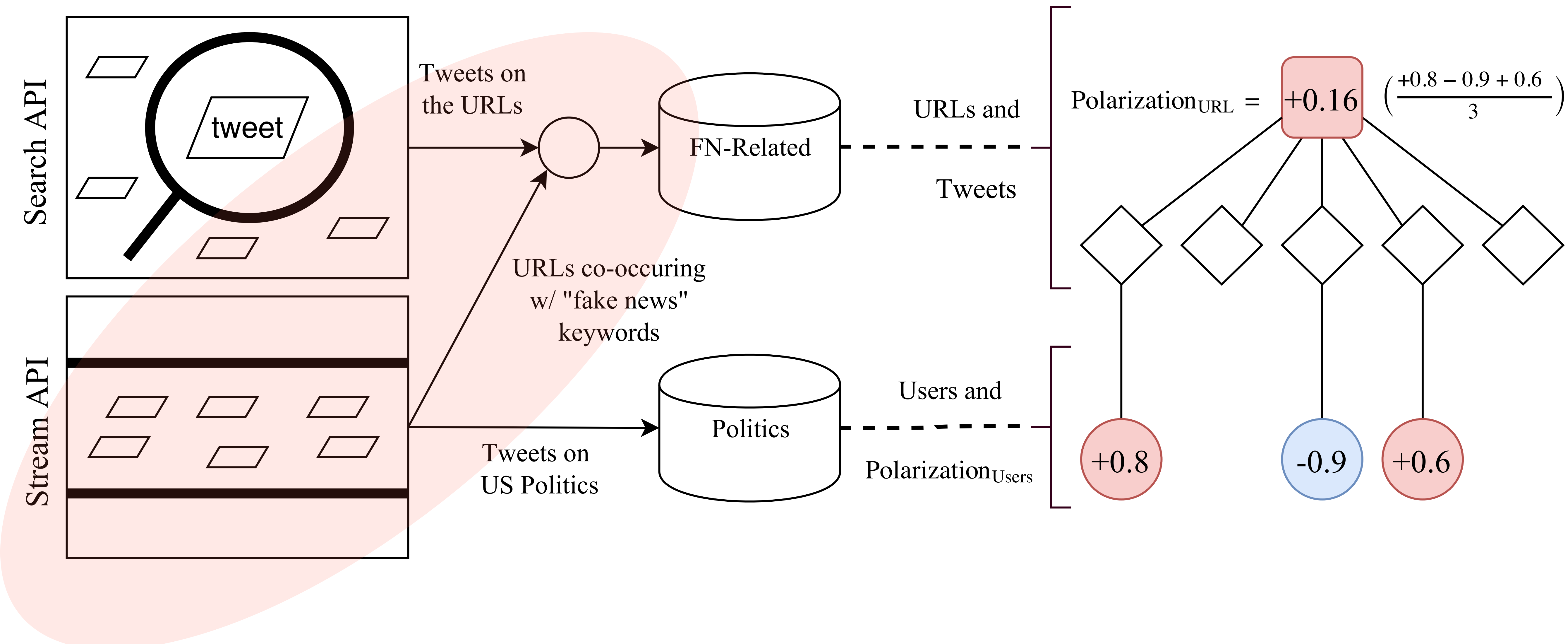
Q1: How is polarization quantitatively related to information perceived as or related to fake news?

***Q2*:** Are users designating content that they disagree with as misinformation?

- We collect a dataset trying to answer this questions in the following fashion:



- We collect the *tweets* with words and hashtags related to misinformation using the stream API.



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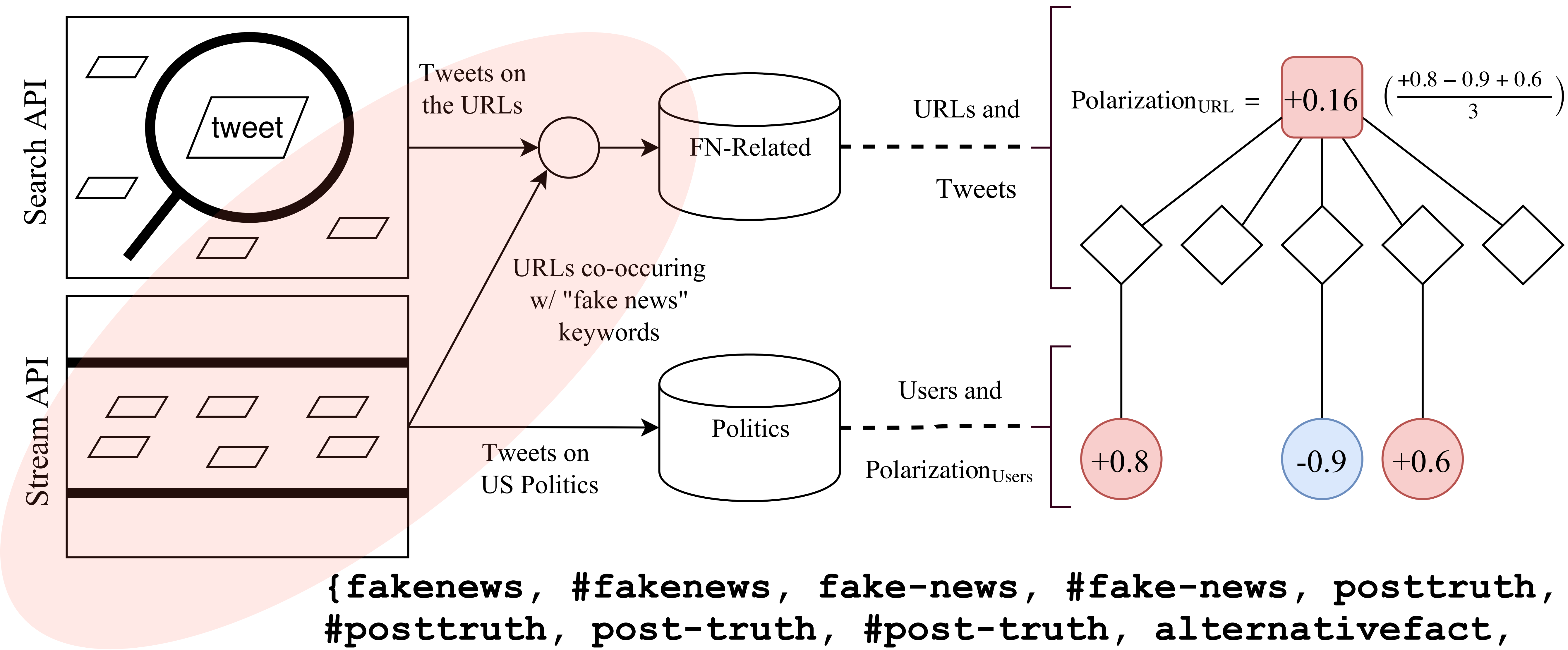

{fakenews, #fakenews, fake-news, #fake-news, posttruth, #posttruth, post-truth, #post-truth, alternativefact, #alternativefact, alternative-fact, #alternative-fact}

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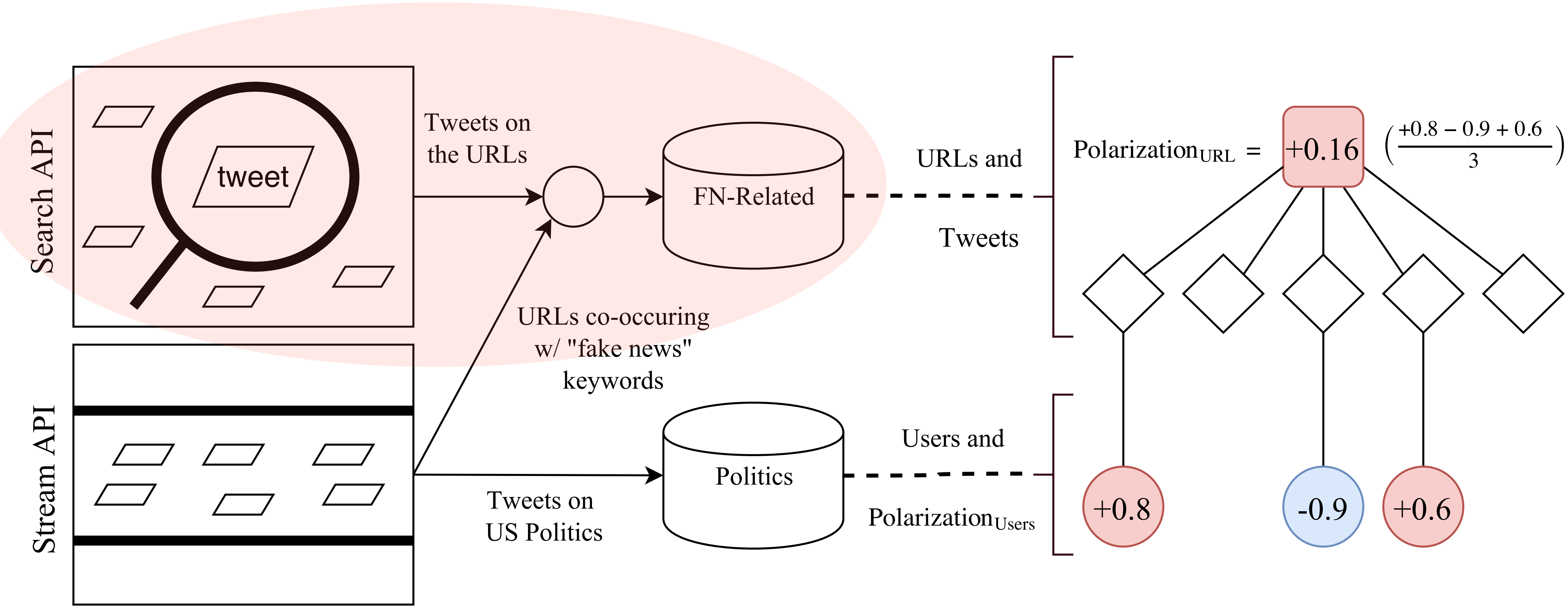
- We use the URLs in the tweets in the search API and find more general tweets about it (not necess. w/ keywords)



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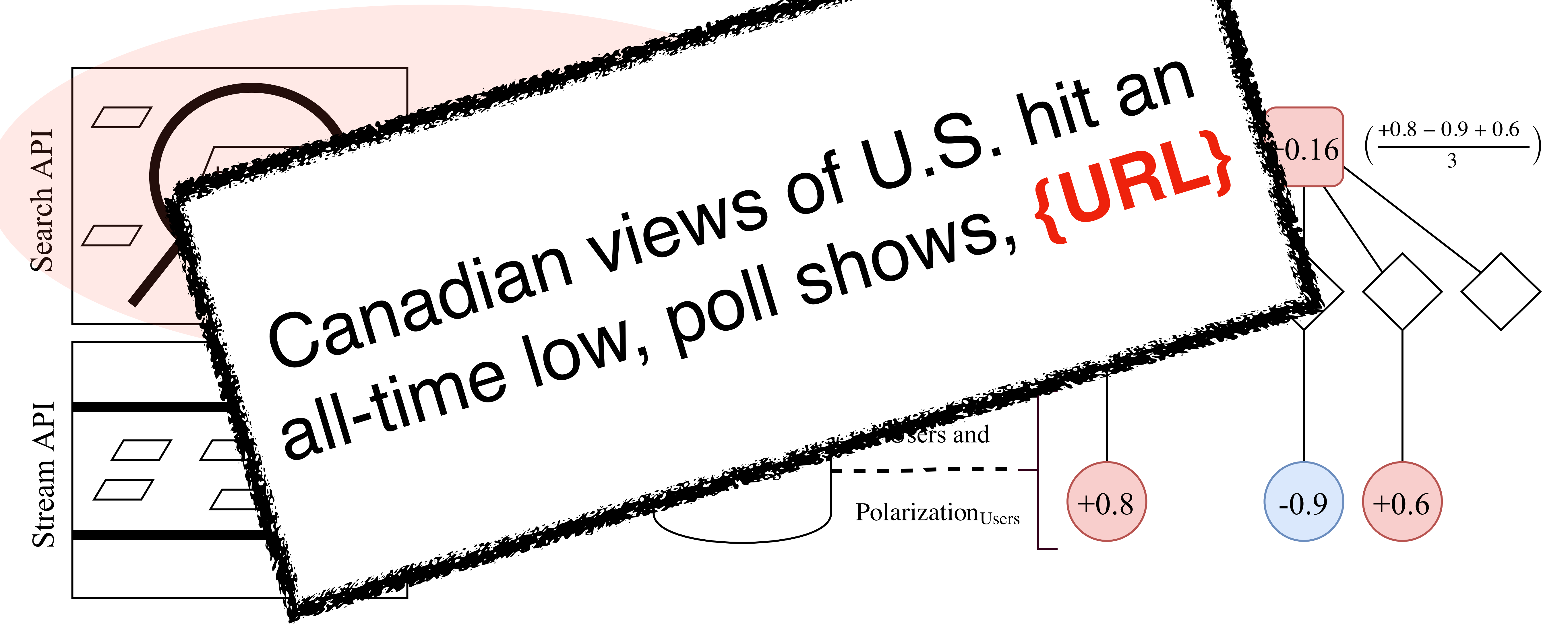
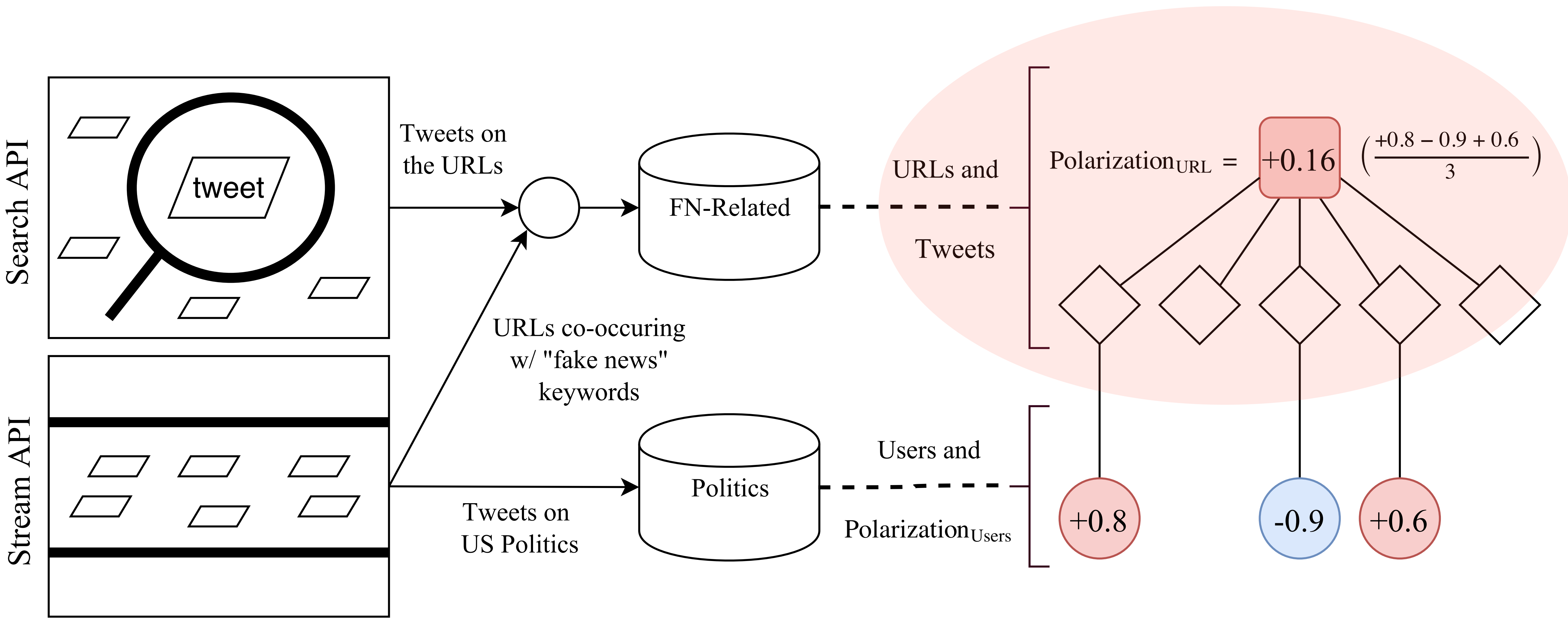
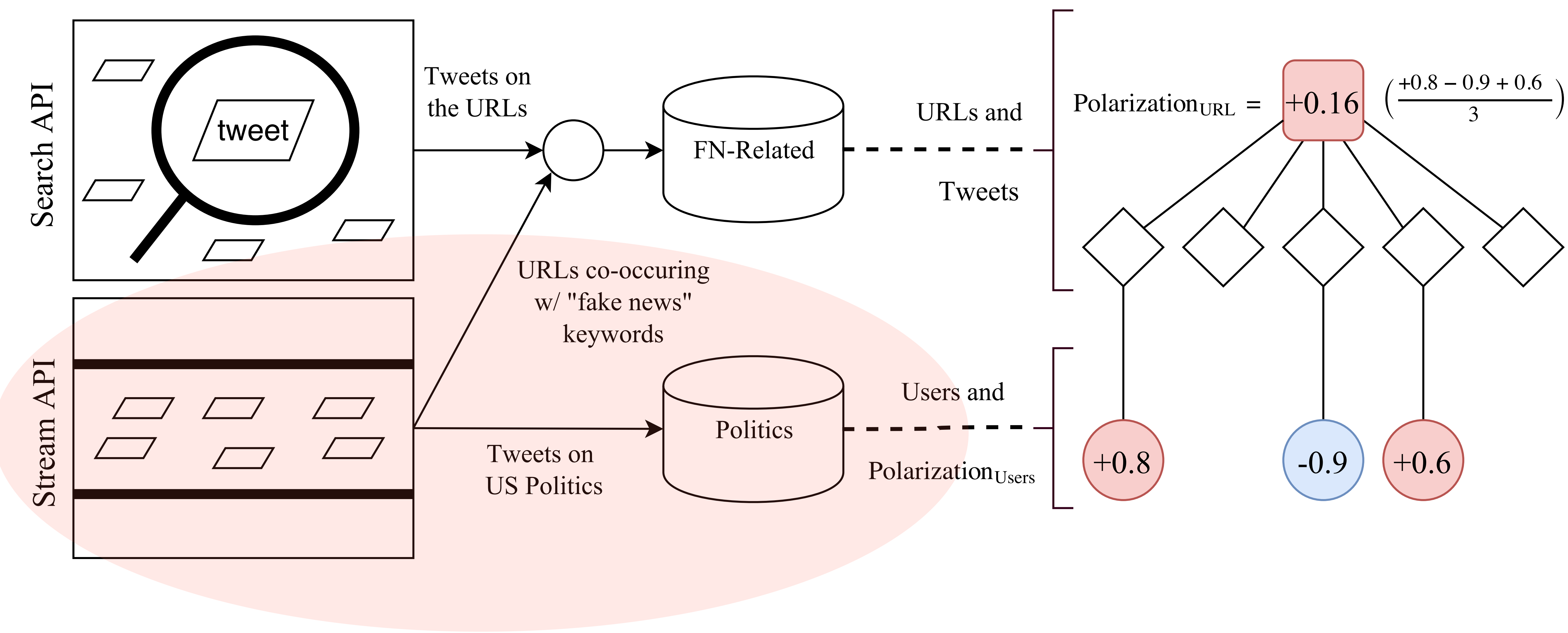


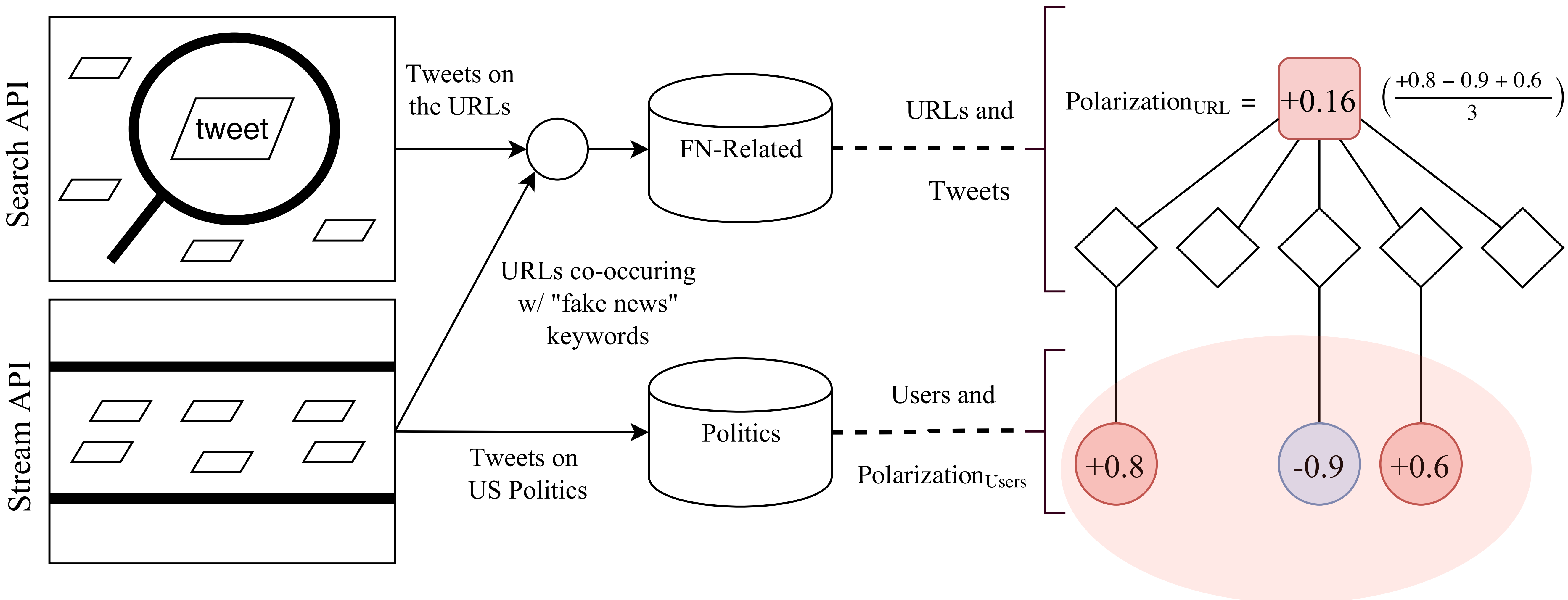
- With this we can manage to get an URL and a many associated tweets.

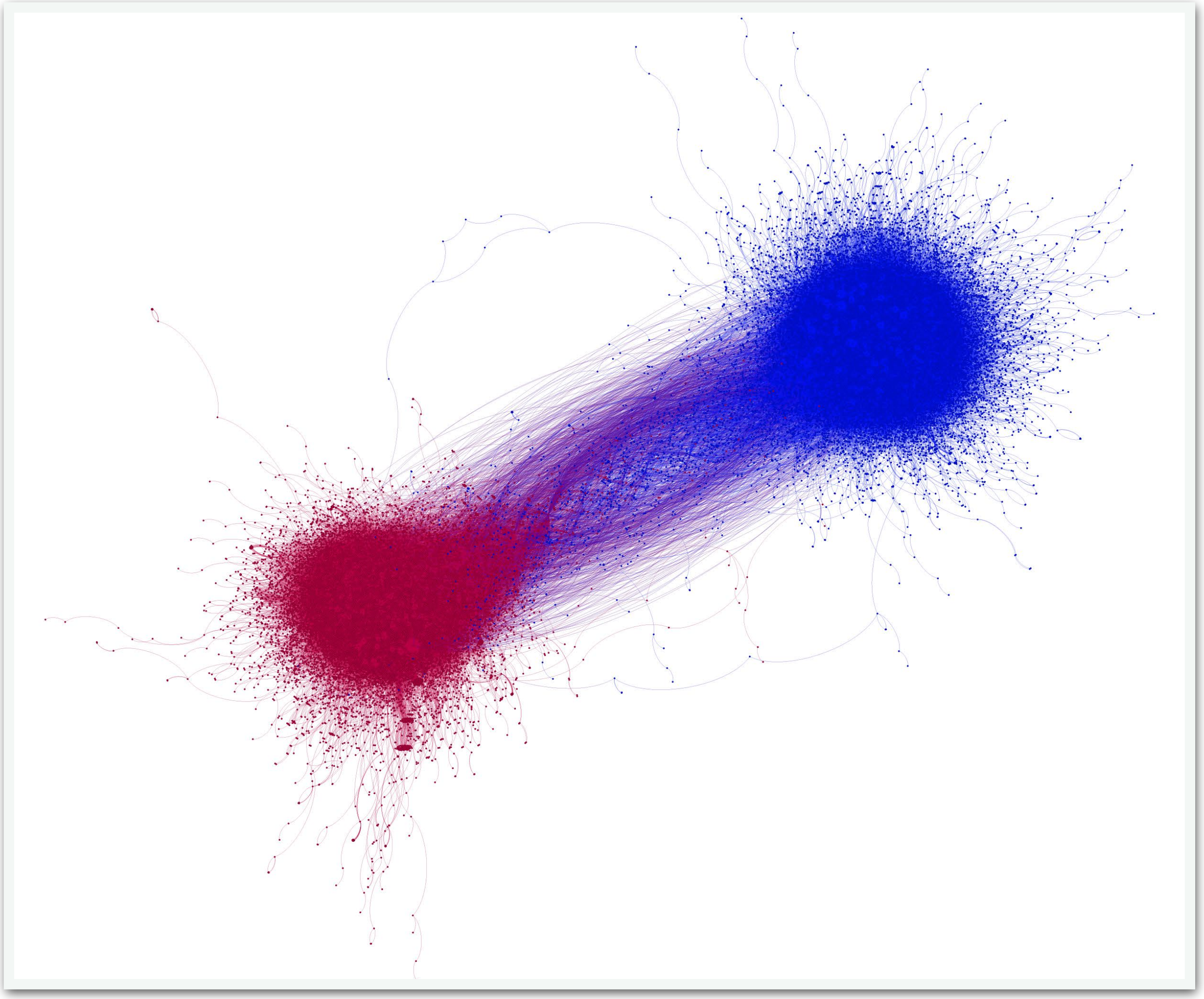


- The second step envolves a bigger data collection in the stream API involving more broad political hashtags



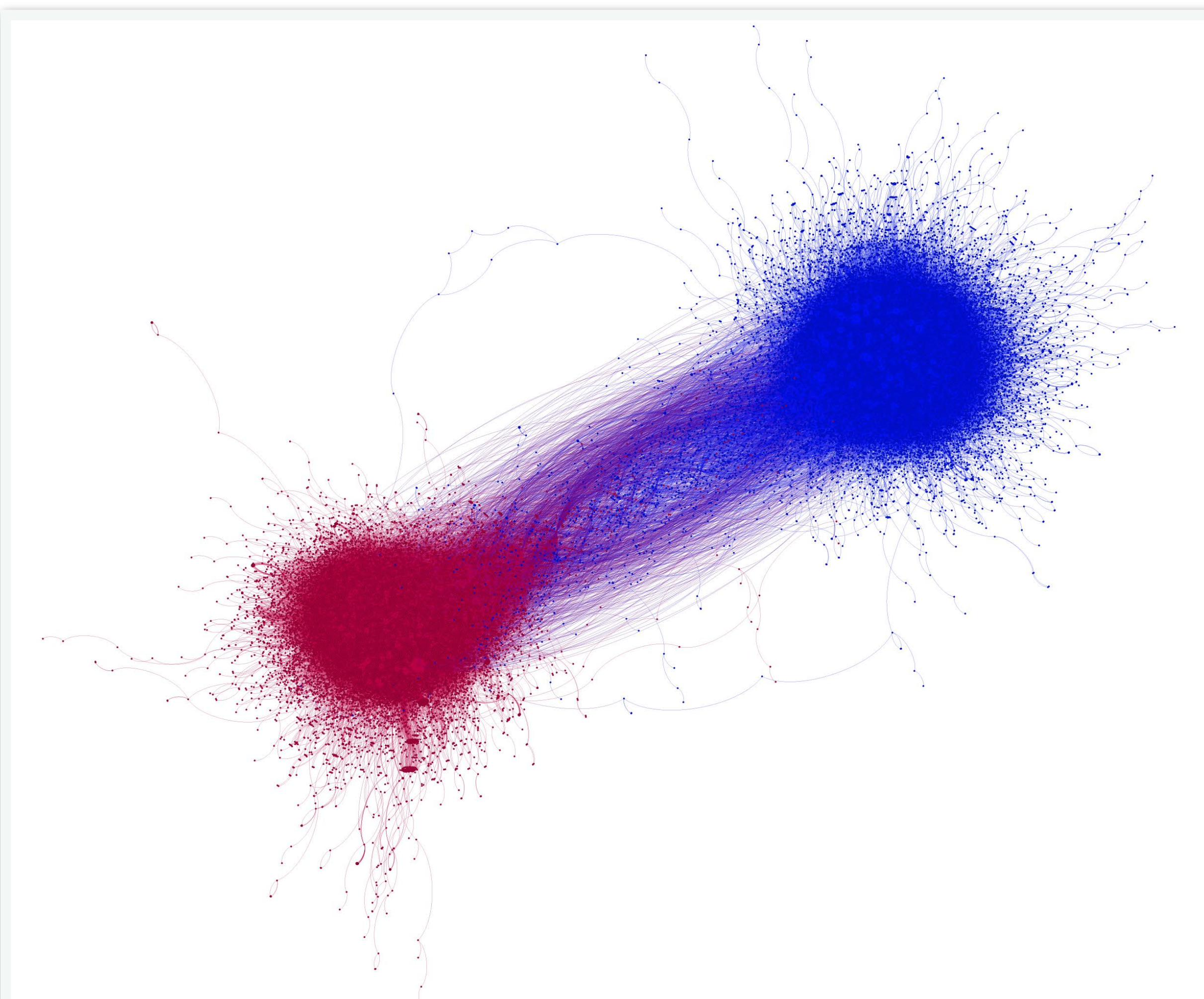
- This allow us to (with an community detection algorithm) get a polarization metric for some of the users





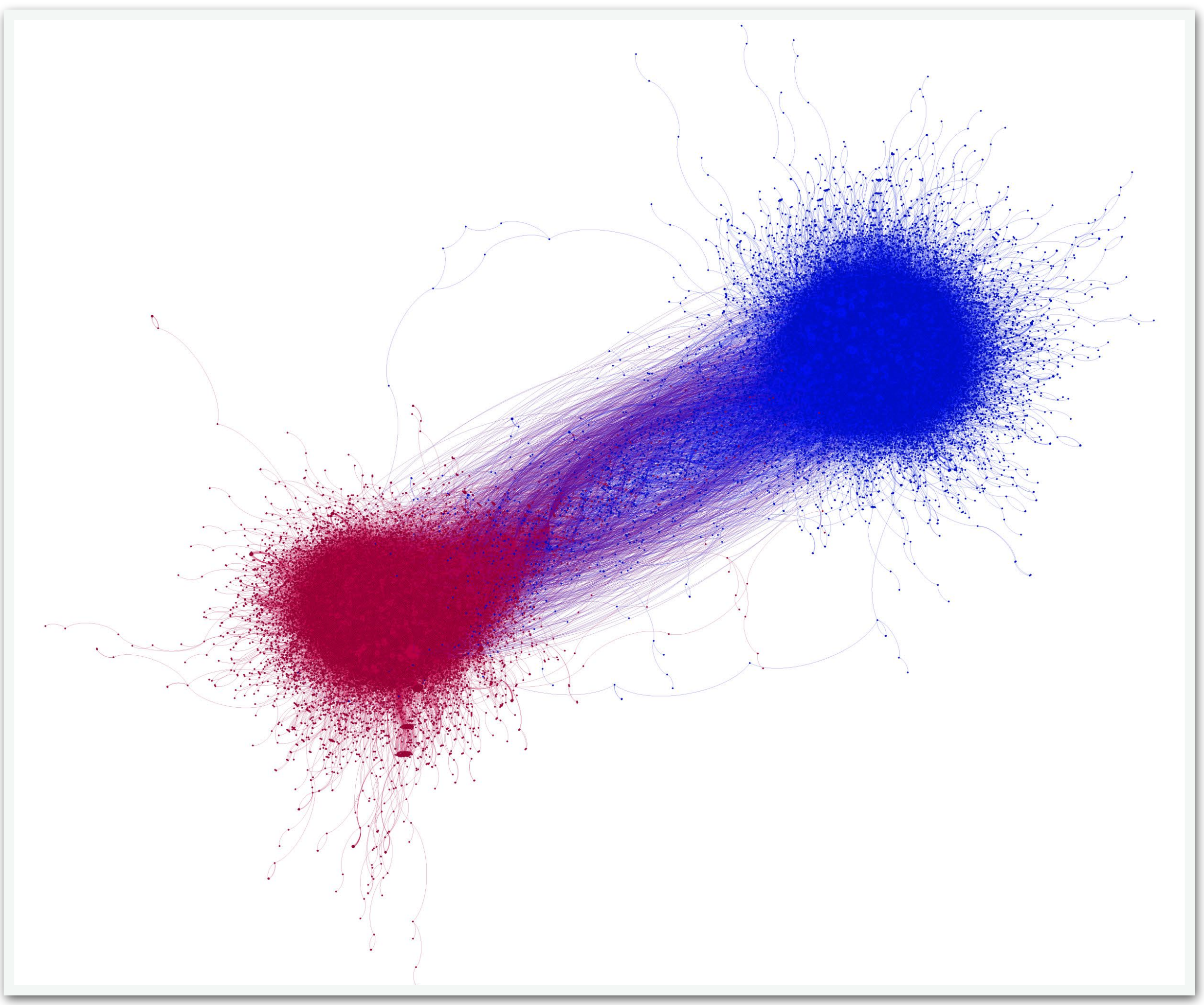
- Assume that the number of communities K formed around a topic T is known

- We build the retweet bipartite graph using the retweets in the collected dataset.



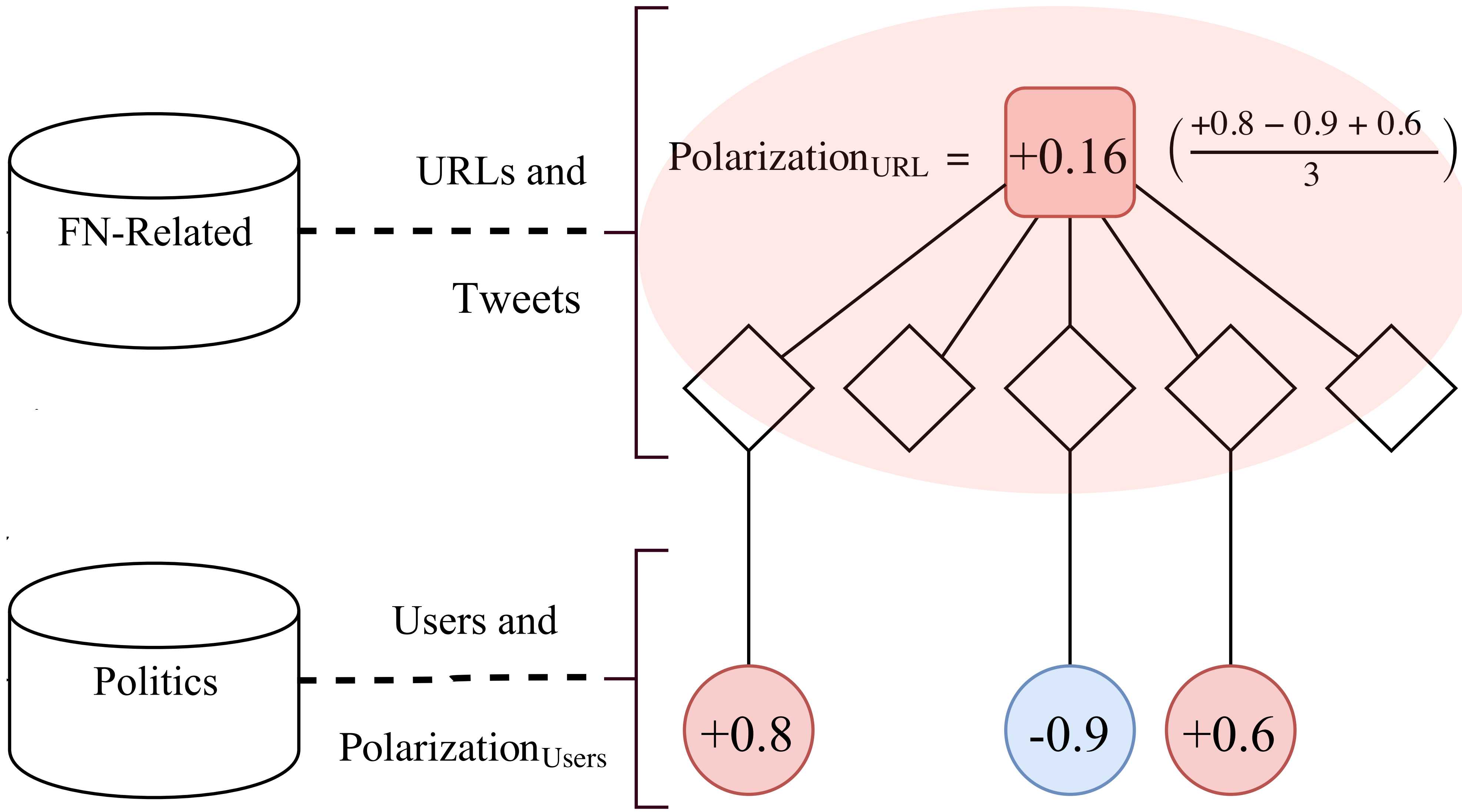
- We select seeds with known political position, (i.e. politicians)

- A random walker departs from each seed and travels, with some probability of restarting from its original

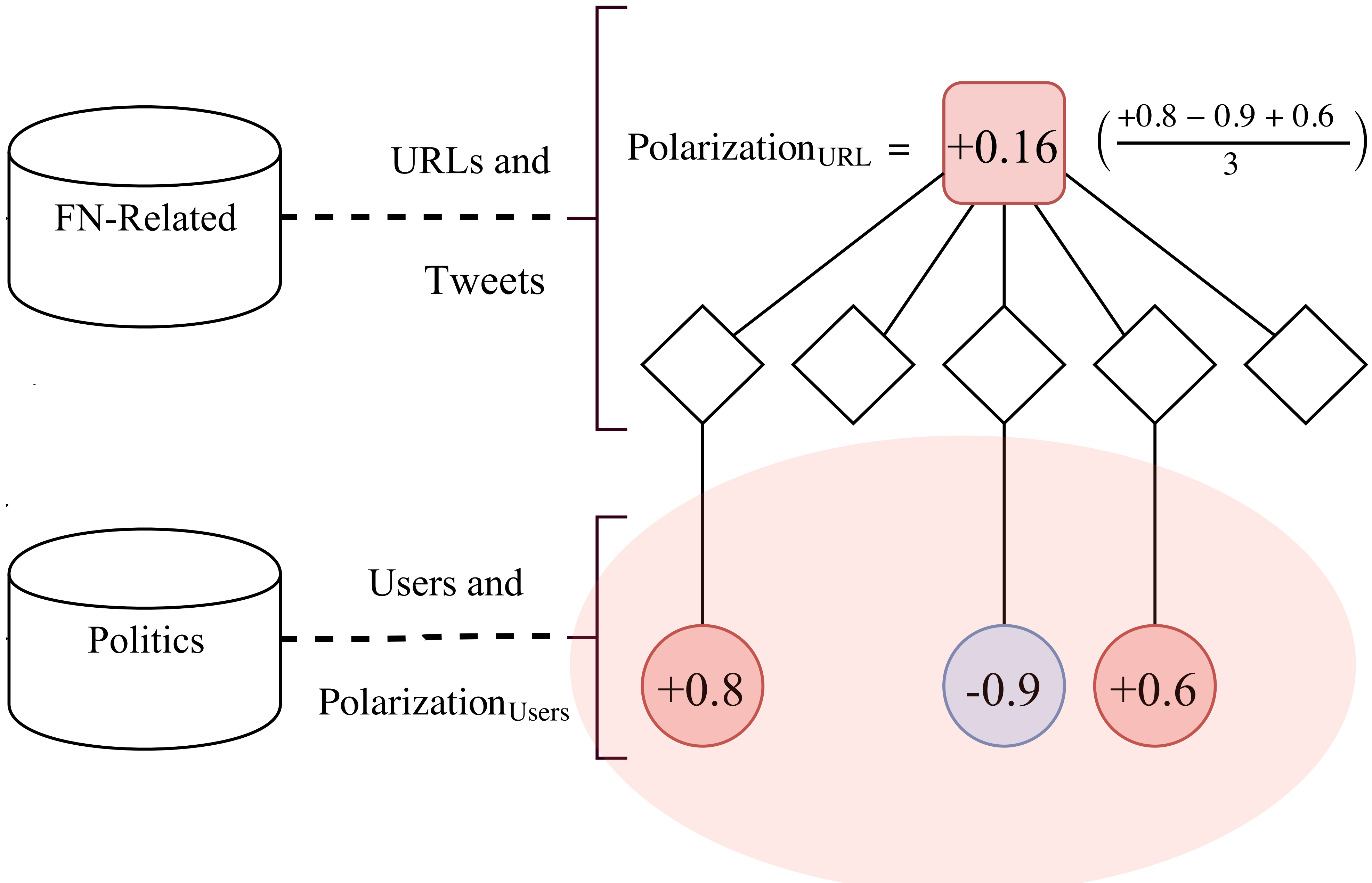


- The relative proximity of each node to the sets of seeds yield a prob. that that node belongs to that community

Method



FN-Related
URLs and
Tweets
Politics
Users and
Polarization$_{Users}$
Polarization$_{URL}$ = +0.16 $\left(\frac{+0.8 - 0.9 + 0.6}{3}\right)$
+0.8
-0.9
+0.6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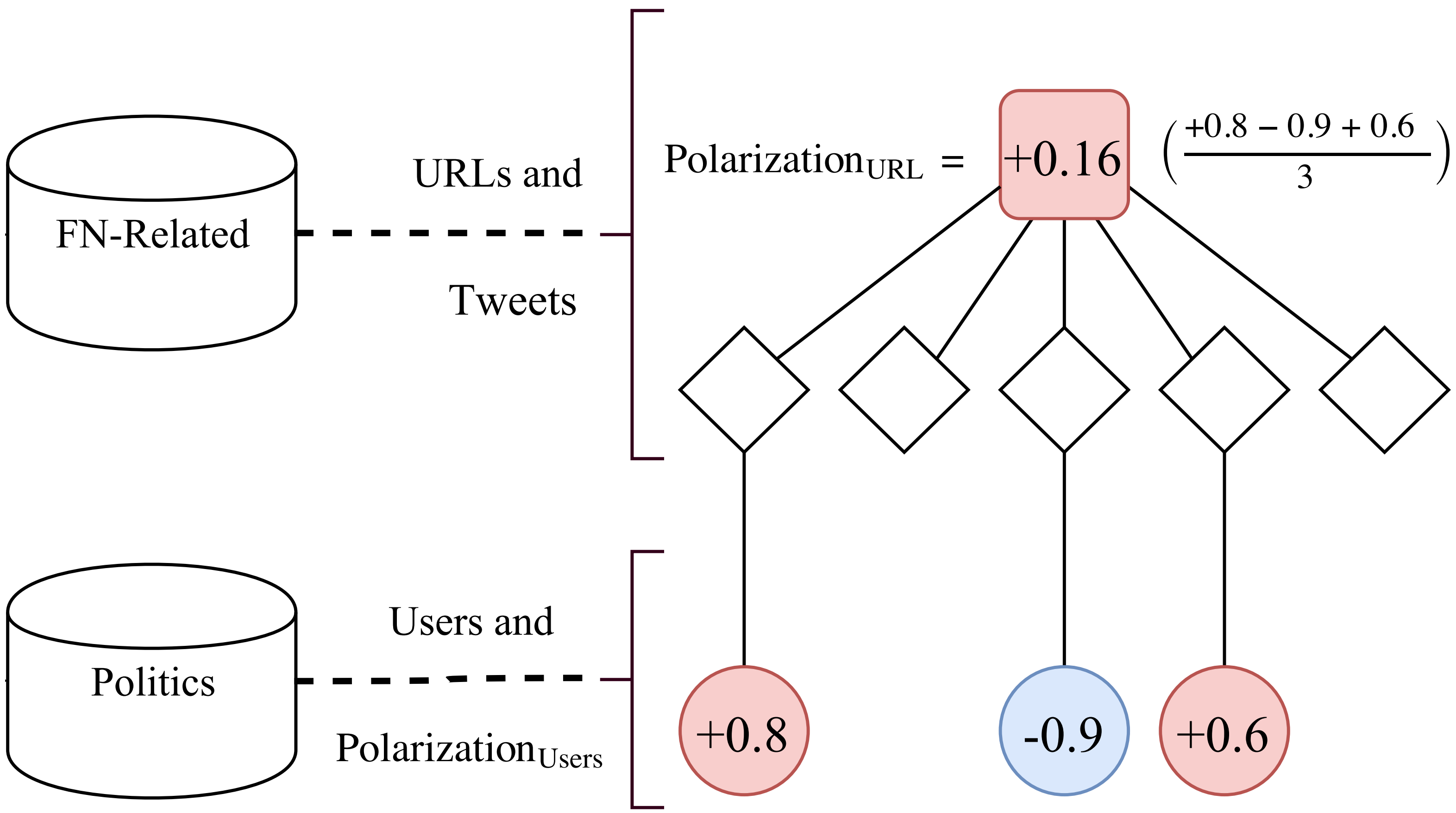
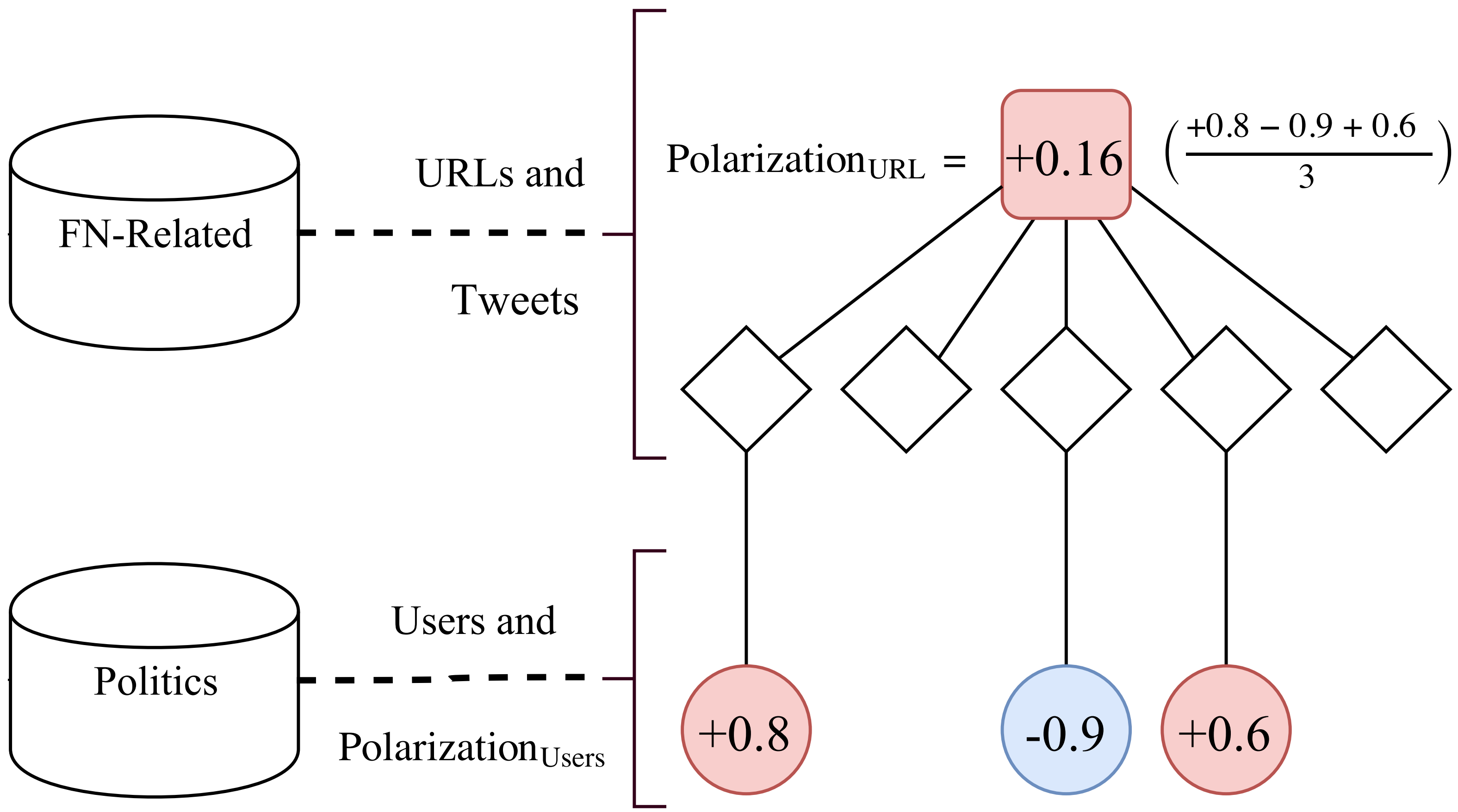


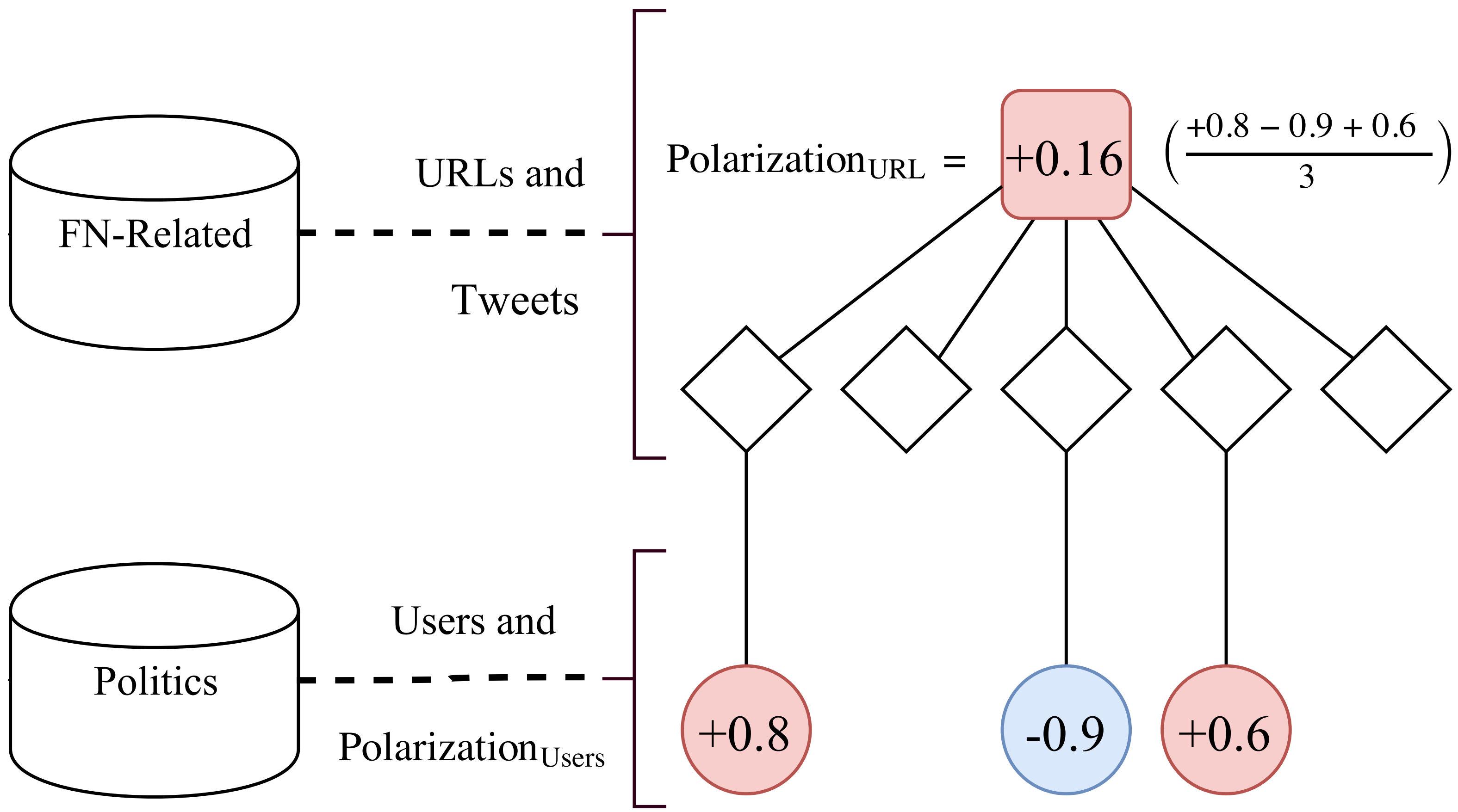
- With this data we:

(i) Estimate users political polarization on different domains.



- With this data we:

(ii) Estimate political polarization of URLs.



- With this data we:

(iii) Qualitatively analyze the domains and the content of the URLs.

- Data collection extracts the political orientation of 374,191 of users that commented some of the collected URL (29%)

	General Statistics				Shared Users		Shared Active Users	
Source	#users	#active users	#tweets	#urls	FN-Related	Politics	FN-Related	FN-Related
FN-Related	374,191	101,031	833,962	109,397	-	29.22%	-	37, 61%
Politics	4,164,604	247,435	246,103,385	-	2.62%	-	15.72%	-

Table 1: General characterization of the data sources. The intersection between the Politics dataset and FN-Related is important as we use it to characterize the polarization of the users, and consequently of the URLs in the FN-Related datasets.

- Although it is a relatively small sample of all the users in a broader context (2.67%), it jumps to 15.72% when we consider only the active users.

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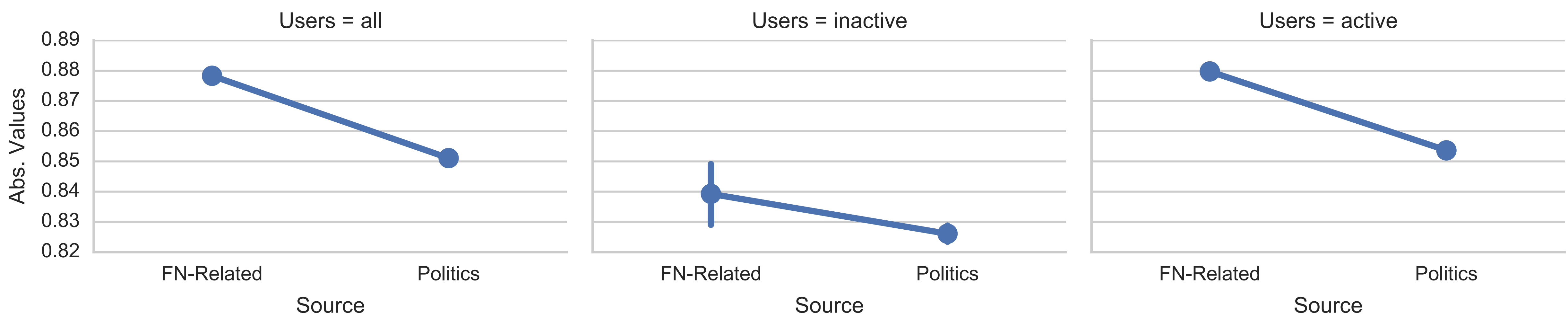
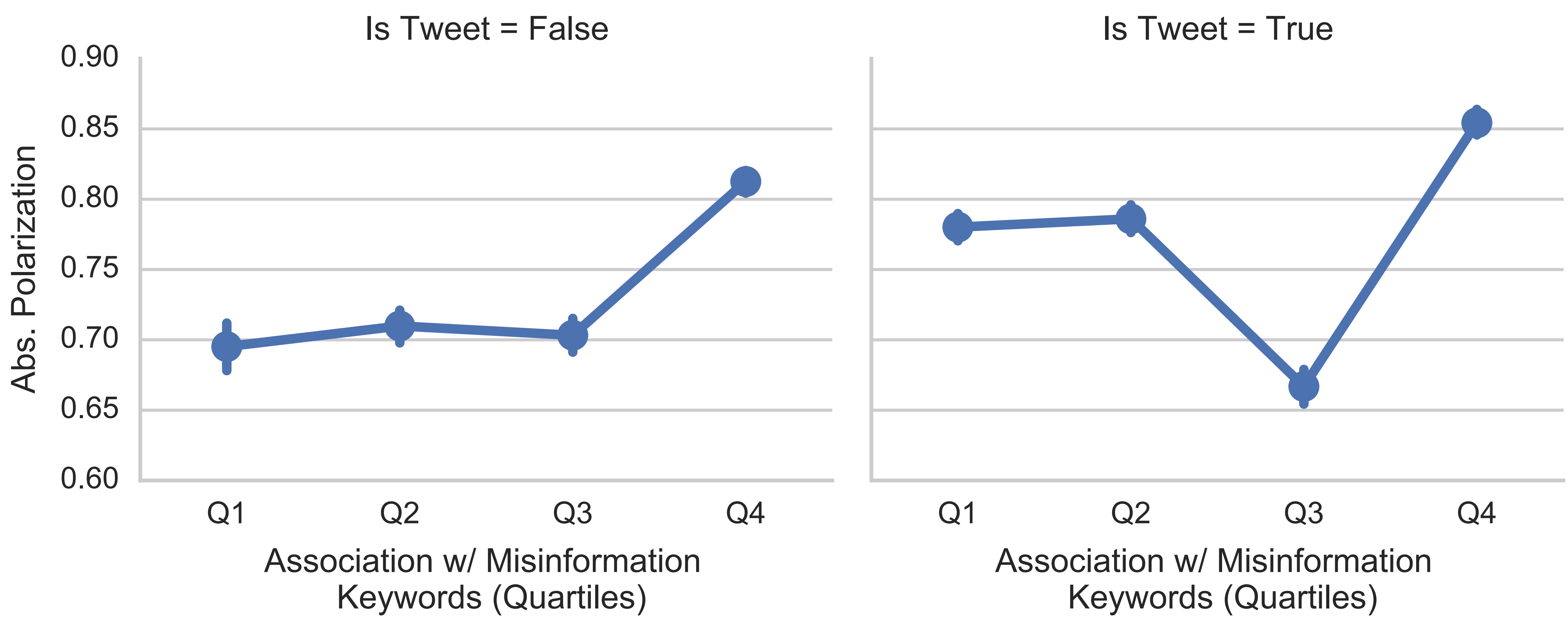
Table 1: General characterization of the data sources. The intersection between the `Politics` dataset and `FN-Related` is important as we use it to characterize the polarization of the users, and consequently of the URLs in the `FN-Related` datasets.

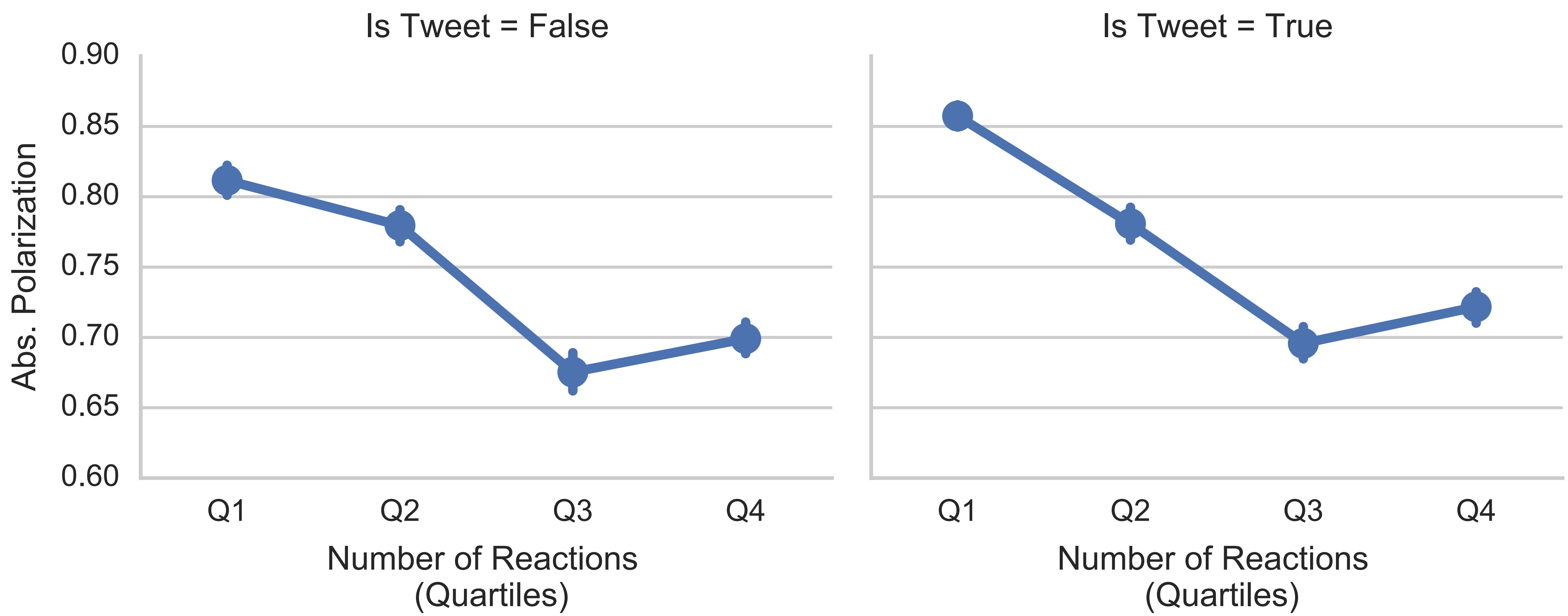
- The users in the fake-news-related dataset are more polarized than in the general politics one. This is evidence that fake-news-related discourse induces polarization.



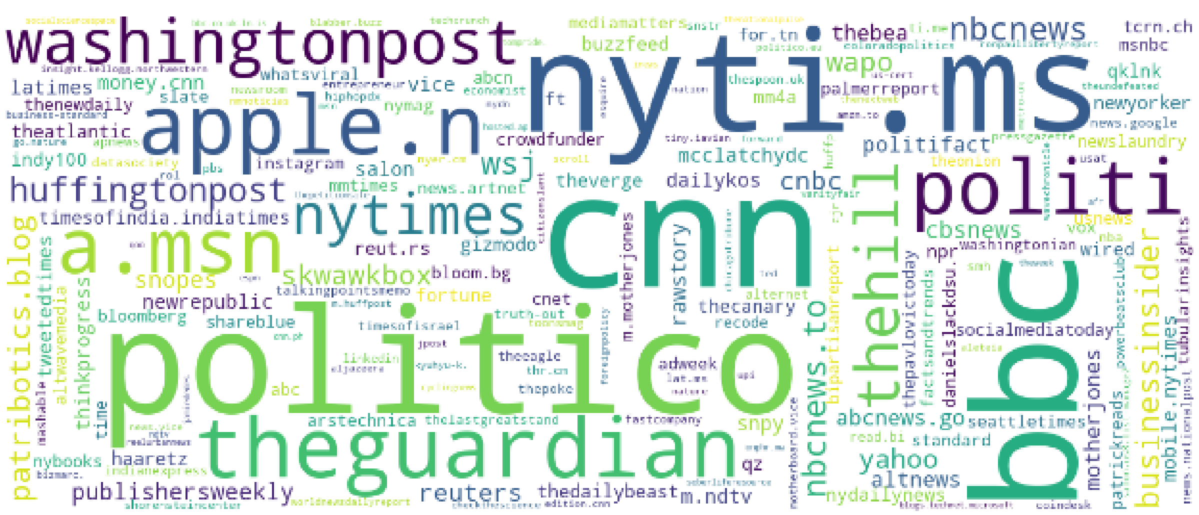
- The polarization grows according to association with misinformation.

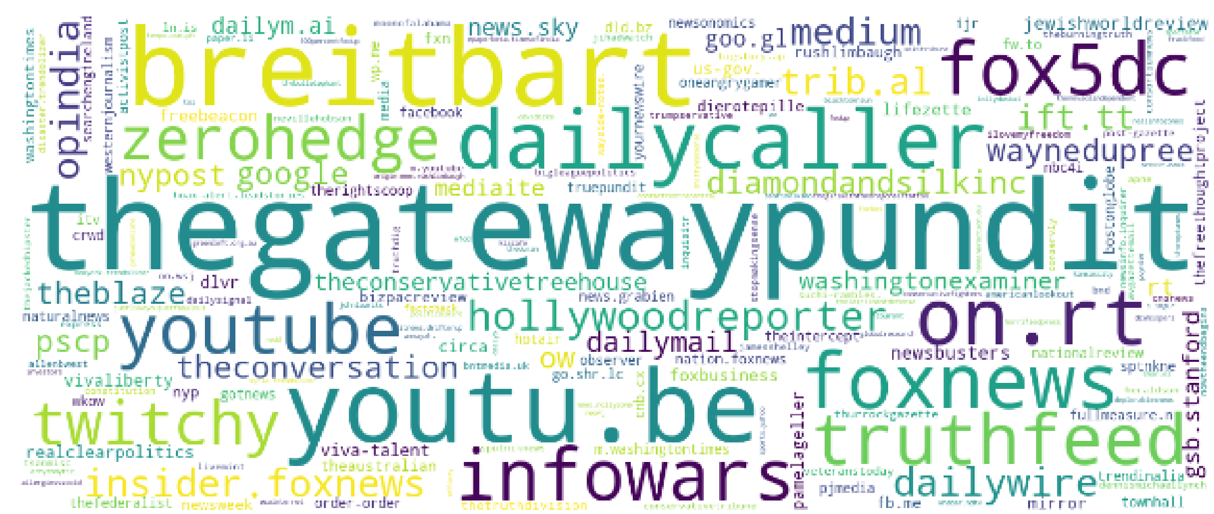


- The polarization decreases with number of reactions.



- People cite sources that they agree ideologically with in this fake-news-related context.





- Qualitatively analyzing top URLs.

{DISMISSING A NARRATIVE}
New York Post: FBI clears
Michael Flynn in probe
linking him to Russia

- Qualitatively analyzing top URLs.

{HUMOUR}
Telegraph: Prisoner dressed as woman in failed escape bid

- Qualitatively analyzing top URLs.

{NEWS FAKE TAGGING}
Raw Story: Family blasts right-wing media for spreading fake news story about slain DNC staffer as Russia scandal deepens

- Qualitatively analyzing top URLs.

{URL FAKE TAGGING}
@realdonaldtrump: The Russia-Trump collusion story is a total hoax, when will this taxpayer funded charade end?

- We present quantitative evidence of various interactions of polarization and misinformation.
- We present qualitative evidence of different uses of misinformation-related tags.

What does this means?

Discussion

- This may present challenges for solutions that use the "wisdom of the crowd" to determine what is fake.
- Polarization may prove itself useful as a feature to distinguish between fake and biased.

- **Future directions**:
  - How to quantify the influence of bias on what is perceived as fake?
  - How to explicitly tell how biased a piece of information is? Should we do this?

Thank You!

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7 DE SETEMBRO DE 1927